RENO-CC: A new system to Fuel Lattice Design in Boiling Water Reactors Using Neural Networks

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Abstract

We show a new system to optimize fuel lattices in BWRs named RENO-CC. The system employs a multi state recurrent neural network (MSRNN) for optimizing a fuel lattice pin-by-pin U235 enrichment distribution. Local Power Peaking Factor (LPPF) and k-infinite (k_∞) are involved in the MSRNN energy function. Both parameters are calculated by the 2D HELIOS transport code for lattice burn-up. Through the iterative process the MSRNN decreases PPF value while k_∞ is kept in a rank of values, at the beginning of lattice life (BOL). The iterative process ends after 20 iterations. If PPF is not lower than limit, RENO-CC applies a fuzzy logic rule in order to recommend if the fuel lattice has an acceptable LPPF value and it might eventually be used in a fuel load. When a fuel lattice is obtained it can be used into a fuel assembly. And eventually, this fuel assembly would be used in the process of fuel load and control rod patterns optimization. So, a 3D core reactor calculation must decide if such a lattice design can fulfill the operation conditions into the reactor core. Preliminary results are shown in this paper.

KEYWORDS: Neural Networks, Fuel Lattice Design, BWRs, Fuzzy Rules

1. Introduction

Fuel lattice optimization is an important step in the fuel load design process. A fuel lattice design with a low local power peak (LPPF), permits better safety margins in the reactor operation. Besides, the final fuel assembly design must fulfill the energy specifications for the cycle operation. A typical fuel lattice is a squared array of NxN rods. Each rod contains some nuclear fuel material as dioxide of uranium, gadolinia or water. Water rods usually have a diameter bigger than the diameter of other material rods. Fuel lattice design consists of assign the materials in the rods in order to fulfill some requirements (see Fig. 1).

In our particular case, we have a fuel pin inventory with several U235 (w/%) enrichments and

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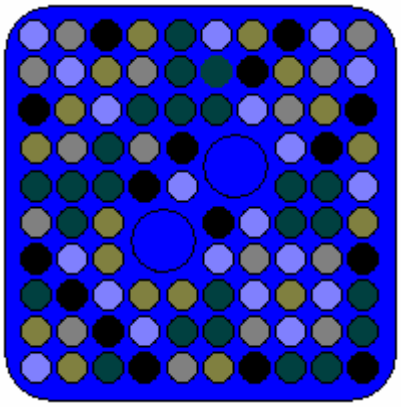
gadolinia concentrations. The optimal fuel lattice is obtained with an adequate U235 enrichment and gadolinia concentrations distribution that minimizes the LPPF and keeps k_∞ in an interval from k_∞^{MIN} to k_∞^{MAX}, at the beginning of the lattice life. In this work, the U235 and gadolinia distributions are determined by using a multi state recurrent neural network.

Figure 1: A typical BWR 10x10 fuel lattice array.



Neural networks have been used in several nuclear engineering problems, for example in fuel management. Gonzalves et al. [1] show a neural network to predict the radial power density distribution in the core and the soluble boron concentration at the end of the cycle, in order to optimize fuel load with a genetic algorithm. Ortiz and Requena [2] used a neural network to predict thermal limits and the effective neutron multiplication factor at the end of the cycle in boiling water reactors (BWRs), and then with genetic algorithms [3] and recurrent neural networks [4], they optimized fuel loadings. Roh et al. [5] used a neural network to predict power levels in a reactor core using real power measures. Erdoğan and Geçkinli used a neural network to predict the fuel bundle power and the effective neutron multiplication factor [6]. And so, with a genetic algorithm they optimize the fuel loading in a pressurized water reactor (PWR). Jang et al. [7] trained neural networks to predict the power in each fuel channel of an eighth core. They used simulated annealing to optimize the fuel load in PWRs. Finally, Kim et al. [8] trained a neural network to estimate the LPPF and the effective neutron multiplication factor at the beginning of the cycle.

In the next section we show a brief description of the recurrent neural network. In section 3, we show the system RENO-CC. In section 4 the main RENO-CC results are shown.

2. The Recurrent Neural Network

Artificial neural networks are biologically inspired computing models. They are composed of a large number of processing elements (named neurons) organized in layers. The most famous neural network model is the multi-layer perceptron, trained with the back propagation algorithm. This neural network has been used to predict parameters, patterns recognition and classification. Currently, there are several neural networks models, for example Kohonen neural network, radial

basis functions neural network, associative memory and recurrent neural networks.

Merida et al. [9] proposed the multi state recurrent neural network (MSRNN) model. This neural network emulates the cooling of a hot crystalline structure. A hot crystalline structure has an energy level according to its atoms excitation. In that situation, there are "holes" between the atoms and it is instable. When the temperature is adequately reduced, the holes between atoms also are reduced and the structure is more stable. An ideal crystalline structure could be such that where holes are minimal and so the most stable.

The MSRNN has one layer of neurons fully connected between them. Each neuron can be seen as an atom in the crystalline structure model. The energy of neural network depends on neuron states. The neuron state is the output value of the neuron. If we change the neuron states in an appropriate way, we can reduce the energy of neural network. The rule of states transition permits to change the neuron states. The energy function measures the energy level of the neural network. It is important to say, that this kind of neural network does not require a training to adjust the weights between neurons. The weights are introduced into the energy function and they are invariable throughout the iterative process. In next section we explain the iterative process.

3. The System RENO-CC

So, for our problem we built a neural network with 100 neurons to represent the 10x10 array. Neuron states can take values of enrichment and gadolinia concentration from the fuel pin inventory and the energy of the neural network is a function of the fuel pin locations. The MSRNN executes an iterative process of 20 cycles.

In Fi. 2, we show a half of the fuel lattice, with neurons numbered. There are three neurons that are not numbered because they do not change their neuron state. In order to make easier the lattice design, it is made with mirror symmetry, as we show in the figure. The MSRNN has a layer of neurons in a 10x10 array, as a fuel lattice. Also, the MSRNN is divided in two parts as fuel lattice.

The energy function is the following:

$$Min \quad EF(NS) = w_1 LPP(NS) + \begin{cases} w_2 \left| k_\infty(NS) - k_{\infty,t} \right| & if \quad \left| k_\infty(NS) - k_{\infty,t} \right| > 0.1 \\ 0 & elsewhere \end{cases} \qquad (1)$$

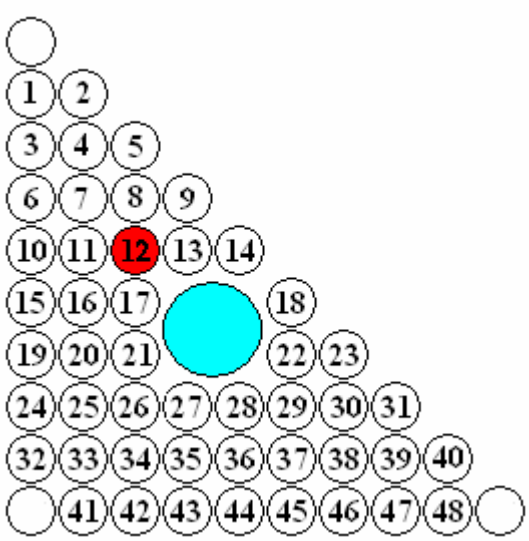
where

- NS is a matrix of neuron states.
- $k_{\infty,t}$ is the target neutron multiplicative factor at BOL.
- w_i are weighting factors, with the following values: $w_1 = 1$, $w_2=1$. That means if k_∞ is in the range, energy function only depends on LPPF.

The iterative process is the following (according to the numbers shown in Fig. 2):

1. All neuron states are initialized according to the uranium average enrichment for fuel lattice proposal. It is to say, U235 (w/%) enrichments and gadolinia concentration are assigned to the pins into the 10x10 array.
2. A random neuron (for example, the number 12) is chosen.
3. For each *neuron* from 1 to 48 do
    a) Interchange their neuron state with that of the neuron chosen in step 2.
    b) Energy function is evaluated and the value is saved.
    c) Return both neurons to their original neuron states.
4. The new global MSRNN will be that interchange of neuron states that produced the lowest energy function value.
5. Repeat steps 2 to 4, twenty times.

Figure 2: Half of a typical fuel lattice



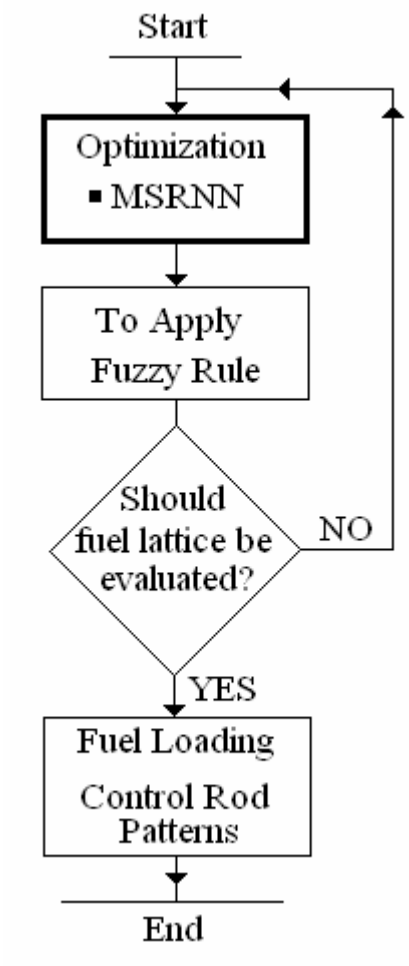
We fixed in 20, the number of maximum iterations, because we have seen that is a sufficient amount to reduce the LPPF.

At the moment, the system only assesses the fuel lattice behavior at the beginning of its life (0 MWd/T). Basically due to two reasons; firstly because HELIOS code [10] spends a lot of calculation time and second due to the maximum LPPF of lattice is presented just at the beginning of the lattice life. In the Fig. 3, we show a flow chart of RENO-CC. In a global view of the matter, after 20 iterations, the best fuel lattice found should be evaluated throughout several burnup points. That is throughout its life. But, what happen if LPPF is not lower than the limit? If the LPPF value is close enough to the maximum limit, may be interesting to study its correspondent fuel lattice. The question is what is the meaning of close enough? At this point a fuzzy logic rule is applied in order to determine if a fuel lattice should be studied. Then the designed fuel lattice might be put into a fuel bundle, and later on in a fuel loading and control rod

patterns for its 3D evaluation.

Currently, we are in the development process of fuel assembly optimization systems. When finally we will have these systems, we are going to couple it with OCOTH [11] and QUINALLI-BT [12] systems, in order to have an optimization system with a wider extent.

Figure 3: RENO-CC flow chart



4. Results

Table 1 shows the inventory of uranium enrichments and gadolinia concentrations used as well as, the neuron state of each one. We used RENO-CC to design fuel lattices with 3.9% of U235 enrichment, including two different gadolinia concentrations.

The neuron states of the MSRNN were initialized according to the requirements. In the Fig. 4, we show this fuel lattice and LPPF and k_∞ values. The number means the %U235 enrichment and

gX means X.0 % of gadolinia concentration. We can see that this fuel lattice has a large LPPF, although k_∞ is into the range from 1.1 to 1.3. In the Fig. 5, the MSRNN behavior through several iterations is shown. In all iterations k_∞ is in the range, for this reason the energy function value corresponds only to its LPPF value.

Table 1: Inventory of uranium enrichments and gadolinia concentrations.

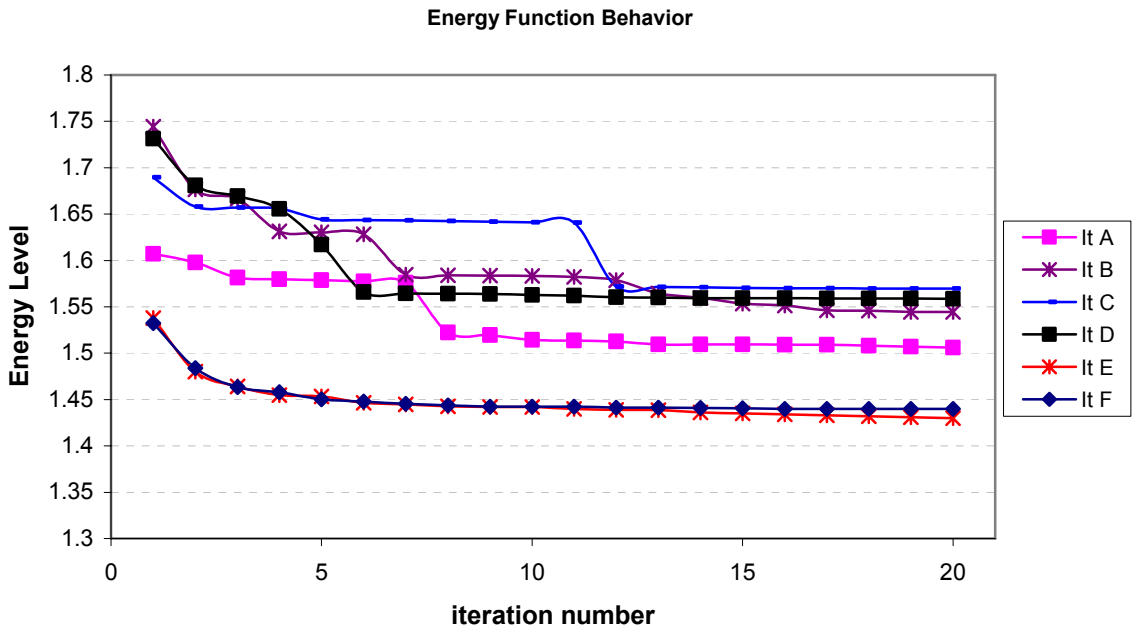
Neuron State	% U235	Gd %
1	2.00	0.0
2	2.40	0.0
3	2.80	0.0
4	3.20	0.0
5	3.60	0.0
6	3.80	0.0
7	3.95	0.0
8	4.20	0.0
9	4.40	0.0
10	4.80	0.0
11	4.95	0.0
12	3.20	2.0
13	3.20	3.0
14	3.20	4.0
15	3.20	5.0
16	3.60	2.0
17	3.60	3.0
18	3.60	4.0
19	3.60	5.0
20	3.60	6.0
21	3.95	2.0
22	3.95	3.0
23	3.95	4.0
24	3.95	5.0
25	3.95	6.0
26	4.40	2.0
27	4.40	3.0
28	4.40	4.0
29	4.40	5.0
30	4.40	6.0

Figure 4: Initial fuel lattice with 3.9% of U235 and 3 rods of 4.0 % and 2 rods of 5.0 % gadolinia

2.00									
3.95	3.95g4								
4.90	2.40	3.60							
4.90	3.60	4.90	3.95						
4.40	3.6g5	3.20	4.90	3.95g4					
4.90	4.40	3.60			4.4g4				
3.95	3.95	2.80			4.90	3.95			
4.90	4.90	3.95	2.40	4.4	3.95	4.90	4.90		
3.95	3.95g5	2.80	2.00	2.0	4.90	3.20	2.80	4.90	
2.00	3.95	4.40	3.60	4.4	4.90	4.40	4.40	4.90	2.00

LPPF = 1.7814 k_∞ = 1.2218 Energy function value = 1.7814

Figure 5: Energy function behavior through several MSRNN iterations.



In the Fig. 5 we can see that iterations from B to D, the LPPF value is greater than 1.45 (pre-established limit value for LPPF). In these iterations, fuzzy logic rule evaluation does not permit they to be studied by a 3D simulation. Instead, iteration A finishes with a LPPF value of 1.506. The fuzzy logic rule evaluation for this fuel lattice yields values of 0.71 (when this value is greater than 0.5, a recommendation of the fuel lattice evaluation is delivered). Finally, fuel lattices have LPPF values of 1.44 and 1.436, that are lower than 1.45. These fuel lattices have a fuzzy rule recommendation of 1.0. In the Fig. 6, the final fuel lattice of iteration E is shown.

In the Fig. 7, we show a fuel lattice map with power levels. In red, the pins with the greatest power, in yellow pins with power lower than the average and pins with power greater than the average power are shown in green. Gadolinia locations and control rod position are also shown. We can see that lowest power levels are in central zones.

4. Conclusions

We have shown a preliminary new system to optimize nuclear 10x10 fuel lattices enrichment and burnable poison distributions. The system named RENO-CC employs a recurrent neural network and the code 2D lattice code HELIOS. This system will be coupled with other optimization system, in order to build a complete system to design fuel loadings. RENO-CC shows good convergence in all realized tests. However, its results are still preliminary.

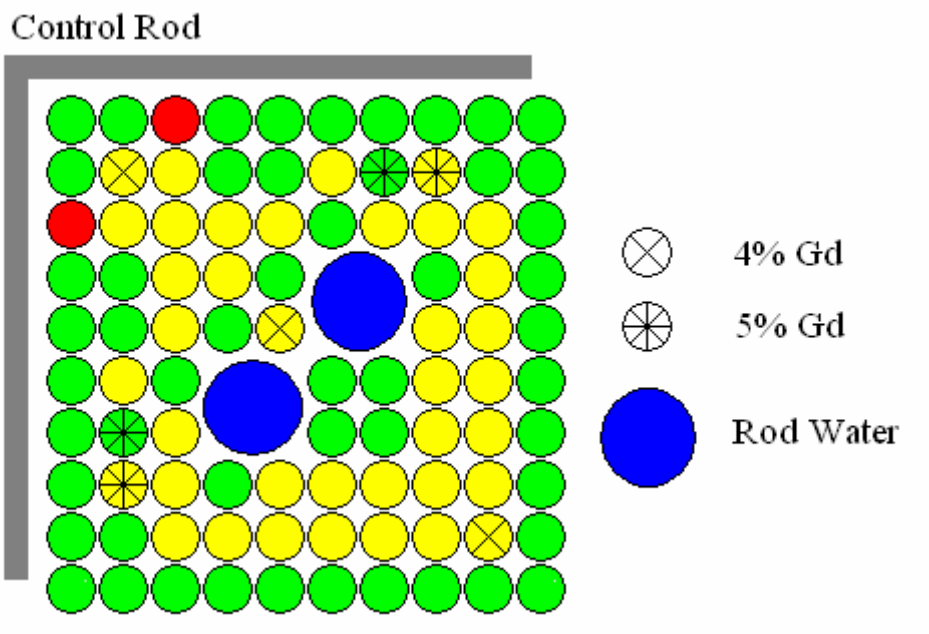
In this study we used a maximum LPPF limit of 1.45; however it is desirable to diminish this value, in order to get better fuel lattices designs that reflect in better operational margins to thermal limits.

Figure 6: Final fuel lattice with 3.9% of U235, 3 rods with 4.0 % and 2 rods with 5.0 % Gadolinia for iteration E.

2									
2.8	3.95g4								
4.9	3.6	3.95							
4.9	4.4	2.8	3.6						
4.9	3.6	2.8	4.9	3.95g4					
4.9	3.95	3.6			2.4				
4.9	4.4g5	4.9			3.95	4.4			
3.6	4.4g5	2.8	2.4	4.4	4.4	4.4	2.4		
2.8	4.9	3.95	4.4	2.4	4.9	4.9	4.9	4.4g4	
2	3.6	3.95	4.4	4.4	4.9	3.95	4.9	3.95	2

LPPF = 1.436 k_∞ = 1.2285 Energy function value = 1.436

Figure 7: Pin power map of optimized fuel lattice.



A RENO-CC execution is very slow due to HELIOS execution. For this reason, currently we are training a perceptron multi layer neural network with back-propagation algorithm to predict LPPF and k_∞ values. So, we will be able to substitute HELIOS code for the trained neural network in order to have a faster optimization system.

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